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A non-representational approach to imagined action

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Abstract

This study addresses the dynamical nature of a “representation-hungry” cognitive task involving an imagined action. In our experiment, participants were handed rods that systematically increased or decreased in length on subsequent trials. Participants were asked to judge whether or not they thought they could reach for a distant object with the hand-held rod. The results are in agreement with a dynamical model, extended from Tuller, Case, Ding, and Kelso (1994). The dynamical effects observed in this study suggest that predictive judgments regarding the possibility or impossibility of a certain action can be understood in terms of dynamically evolving basins of attraction instead of as depending on representational structures. © 2002 Cognitive Science Society, Inc. All rights reserved.

Keywords: Dynamical systems theory; Action possibilities; Imagination; Representation

1. Introduction

The ability to think about the outcome of a yet to be performed action seems to necessitate a representational explanation. It seems difficult to explain this ability unless one assumes that the system constructs a model of the situation, represents the imagined action, and concludes on the basis of the ensuing representational structure whether the goal can be achieved by means of the action or not. In this paper, we aim to question this representational presupposition by investigating the potential of dynamical systems theory (DST) to model imagined actions. According to some (but not all) proponents of DST, a *non-representational*

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account of behavior is possible and in many cases more fruitful for understanding the underlying causal processes (Kelso, 1995; Keijzer, 2001; Port & Van Gelder, 1995; Skarda, 1986; Skarda & Freeman, 1987; Thelen & Smith, 1994; Van Gelder, 1995, 1998). Within DST, the behavior of a system is analyzed as an emergent property of the interactions between its sub-systems. During the last decade, the tools of DST have proven to be valuable assets for understanding behavior emerging out of multiple interacting components. This behavior ranges from rhythmic movements of fingers and hands (cf. Amazeen, Amazeen, & Turvey, 1998; Beek, Peper, & Stegeman, 1995; Haken, Kelso, & Bunz, 1985; Jagacinski, Beek, & Peper, 2000) to the temporal patterns of social interaction (cf. Schmidt, Carello, & Turvey, 1990; Vallacher & Nowak, 1994).

It is often considered to be difficult to apply DST to what could be considered to be genuine cases of *cognition* (see, however, Haken, 1990 on pattern recognition; Thelen, Schöner, Scheier, & Schmidt, 2001 on the A-not-B task; Townsend & Busemeyer, 1995 on decision making; Vallacher, Nowak, & Kaufman, 1994 on dynamics of social judgment). Indeed, DST has been challenged explicitly to try to deal with more “representation-hungry” domains (Clark & Toribio, 1994; see also Clark, 1997, pp. 166–170). One such domain, according to Clark, involves the class of cases that “include thoughts about temporally or spatially distant events and *thoughts about the potential outcome of imagined actions*” (Clark, 1997, p. 167; our emphasis). We consider this challenge to be a rather formidable but justified one. In the present paper, we aim to indicate *a possible path* along which one can attempt to answer the challenge by Clark. We explore whether and how participants’ verbal reports about imagined actions can be understood from within a DST approach. This paper presents an example of how this path could be empirically validated.

1.1. Categorizing imagined actions

The task we will be focusing on is the judgment whether or not it is possible to displace a distant object with the aid of a hand-held rod. While standing at a fixed position participants held a rod and were asked to *imagine* whether or not they would be able to displace an object with the rod. They expressed their judgment (by responding either “yes” or “no”) without actually trying to reach and displace the object. Thus, participants had to imagine the outcome of an action and discriminate between those instances in which the action is deemed to be successful from the ones that are not. Regarding our task, we would like to stress that the participants engage in a categorization not of stimuli or actions, but of imagined actions, in the sense that ideas and judgments about possible states or events in the world are formed without actually performing the action. The participants give judgments about an action-dependent situation that is not present to their senses.

From a Gibsonian perspective, the task can be interpreted as requiring participants to judge whether an object affords to-be-displaced by a given rod. The term “affordance” denotes the possibilities for action of an environmental layout with reference to a person’s capabilities for action (Gibson, 1979; Turvey, 1992). Warren’s (1984) investigation of affordances in relation to stair climbing provides an approach that is in some respects congenial to our own. He presented participants with slides of wooden stairways with different riser heights and asked their judgment regarding the climbability of the stairs. From this perspective, our investigation

could be interpreted as related to the perception of affordances or to, as Warren (1984, p. 699) puts it, as a form of “perceiving the ‘work to be done.’” Yet, this is not contradictory with our interpretation of the task as being representation-hungry, for precisely from the traditional cognitivist perspective it has been argued that the direct pickup of affordances is, ultimately, a representation-laden process (Fodor & Pylyshyn, 1981). The reason that we do not interpret our task in terms of affordances is first of all that we want to stay clear from the long-standing debates that surround this notion (e.g., see the discussion between Fodor & Pylyshyn, 1981; and Turvey, Shaw, Reed, & Mace, 1981). Moreover, from a Gibsonian perspective one would search for the invariances in the ambient array and how this information specifies an action (cf. Michaels, Zeinstra, & Oudejans, 2001; Turvey, 1996). As Warren (1984) did for the stair climbing task, we could search the invariant that observers use in our task. To do this, one could, for instance, vary the properties of the to-be-displaced object, or properties of the rod other than length. However, in the present paper, we aim to find a way of answering Clark’s representation-hungry challenge and we are less interested in the identification of the variable that guides the judgment in this specific task. Although, we were partly inspired by the Gibsonian perspective and we see the intuitive connection between this approach and our work, we think that our major aim requires another approach. In agreement with Michaels and Beek (1995), who evaluate a Gibsonian approach and a dynamic systems approach for understanding perception and action, we believe that each approach fits its own domain of questions. Given our interest in understanding how the dynamics in our task can explain the imagining of the outcome of an action we take the dynamic systems approach as our starting point.

Yet another perspective on the nature of the task can be derived from noting the similarities between what participants have to do in our task and aspects of the *preparatory phase* of an act where an individual has to judge whether the intended action is possible or not. In this respect, our task could be considered as an example of prospective control. Reaching requires *anticipating* forces and *exploiting* the joints available for the action. This implies that judging whether or not a reach is possible requires perceiving *prospectively* how relevant variables will affect the action. Hence, the judgment of the (im)possibility of an action is a complex problem in which a large number of variables and their interactions need to be taken into account. However, there is a subtle but important difference between actually performing a displacement task and the circumstances in our experiment. In the current task, participants have to *imagine* whether the displacement is possible with the rod; participants never actually displace the object with a given rod. This implies that at no instance they can rely on proprioceptive or visual feedback about the accuracy of their judgment. This is completely different from a situation where at any instant the action can be adapted or even aborted given the information about the action that becomes available in the act. Thus, the constraints on the judgment are much tighter in the present judgment situation than in a situation where the displacement actually is performed. No feedback is available which implies that participants can only rely on how they imagine their action possibilities with the rod.

What are factors that participants should use in the present imagination task? Judging whether a rod would enable displacing an object from a certain distance requires prospectively establishing not only the length of the rod but also the maximally possible extension of the arm and the forward bending possibilities of the trunk and legs while controlling the rod.

Hence, judging whether a rod can be used to displace an object is not just simply matching the length of the rod to a reference length (i.e., the distance to the object) but judging whether there is a “posture + rod” that can bridge the gap to the object. Participants have to imagine whether they can control the rod during displacement with a posture that maintains balance. The posture that is possible depends on the properties of joints and muscles that perform the action. Making an accurate judgment regarding the (im)possibility of a reach with a rod involves (a) detecting information about the forces that operate on the body, as well as (b) detecting information about the joints and muscles available for performing the action.

When performing actions, upcoming forces are detected and postural adjustments take place to maintain balance given those forces. Several researchers have measured postural adjustments and muscle activity before and after the start of fast shoulder flexions bringing an arm at the side to the horizontal (Aruin & Latash, 1995; Bouisset & Zattara, 1981, 1987; Brown & Frank, 1987; Horak, Esselman, Anderson, & Lynch, 1984; Lee, 1980; Lee, Buchanan, & Rogers, 1987; Van der Fits, Klip, & Van Eykeren, 1998; for an overview see Massion, 1992). In general, these studies report an increase in EMG activity of postural muscles prior to or in an early phase of the arm movement (depending on condition); this suggests that this activity has an anticipatory component. If load increased, the EMG activity increased or the onset of the anticipatory activity was earlier, dependent on condition (Aruin & Latash, 1995; Bouisset & Zattara, 1987).

However, not just the forces are important, but also the joints involved in the completion of the act. In several studies, the actual maximum reaching distance is compared to the perceived or judged maximum reaching distance. Several studies report an overestimation of the judged maximum reaching distance when only one joint (i.e., the shoulder) is to be used (Carello, Groszofsky, Reichel, Solomon, & Turvey, 1989; Robinovitch, 1998). In that case it seems that participants judge the maximum reaching distance as if more joints, such as the hip and ankle, are also available to make the reach (cf. Rochat & Wraga, 1997). This implies that the question of how many joints are available for an act is important for the judgment concerning a reaching possibility.

Bongers and co-workers (Bongers, 2001; Bongers, Smitsman, & Michaels, 1998, 1999) studied postural adaptations when reaching with rods and whether postures were anticipated. They asked participants to hold a rod with the tip in the air, walk toward an object, choose a place to stop, and displace the object with the rod's tip. In different experiments length, mass and mass distribution of the rod and size of the to-be-displaced object were varied. Those manipulations of the rod should affect the posture with which the rod could be controlled and, thus, should be anticipated in the selected distance to the object. It was found that not only the length of the rod but also the required posture affected the chosen distance to the object. In other words, participants prospectively adapted the distance according to the length provided for by “posture + rod.” The early adaptation of the actions suggests that participants can use similar information when they have to imagine the outcome of an act. On the basis of this, we argue that participants judge posture + rod-length when they imagine whether displacement with a rod is possible. Therefore, imagining postural aspects (for instance, controlling the rod and maintaining balance) are important in our task. So, our task can be called representation-hungry because it requires participants to engage in a prospective form of perception without receiving feedback, which, moreover, involves the combination of information across a variety of

domains (i.e., visual and kinaesthetic) in relation to an estimation of possible body posture, which involves the anticipation of forces.

Finally, Heft (1993) provides what could be taken as an empirical test of our claim that the task requires more complex forms of cognition than pure perceptual comparison. The test is based on the phenomenon of overestimation of reaching distance. According to Heft (1993) under certain circumstances the estimation of reaching distance is less precise than what may be expected on the basis of perception–action abilities of individuals. He suggests, based on Helmholtz's (1925) concept of 'unconscious inference' that "when individuals 'intellectualize' in the process of making a perceptual (i.e., nonintellectual) judgment (...) their performance will be adversely affected" (Heft, 1993, p. 258). His experimental results indicate that overestimations of reaching distance "reflect the intrusion of nonperceptual processes" into more basic cognitive processes (Heft, 1993, p. 266). Imagining the outcome of an action is an example of such 'nonperceptual' processes. Following Heft, then, we propose that the finding of substantial overestimation of reaching distance would provide at least suggestive evidence that people are taking a more cognitive, or representation-hungry approach to the task. We will return to the issue of overestimation of reaching distance in Sections 4 and 5.

In all, we claim, our task presents a simple, yet clear case of a representation-hungry phenomenon. We wish to contrast our dynamic account of this task with a traditional computational account according to which the relevant variables are represented within the cognitive system, which then computes whether the intended or imagined action will lead to the desired result (e.g., by comparison of the situation with an internal standard). In the case of our task this would mean that a participant is assumed to be primarily engaged in a comparison between the representations of the length of the rod, the postural possibilities and the estimated distance to be bridged. The successfulness of the imagined action is thought to be established on the basis of calculations transforming these representations.

1.2. Representations: are they always necessary?

The notion of "representation" has for a long time been a corner stone of cognitive science. A definition that is often used in recent debates on representation is given by Haugeland (1991, p. 62):

A sophisticated system (organism) designed (evolved) to maximize some end (e.g., survival) must in general adjust its behavior to specific features, structures, or configurations of its environment in ways that could not have been fully prearranged in its design. [...] But if the relevant features are not always present (detectable), then they can, at least in some cases, be represented; that is, something else can stand in for them, with the power to guide behavior in their stead. That which stands in for something else in this way is a *representation*; that which it stands for is its *content*; and its standing in for that content is *representing* it.

Another famous interpretation is given by Newell (1980, p. 156):

An entity X designates an entity Y relative to a process P, if, when P takes X as input, its behavior depends on Y.

The basic idea of these two definitions is the same. The two most important features of representations are, on this account, that a representation *stands in* for something not (reliably)

present, and that the system *uses* the representation in order to guide its behavior. According to traditional cognitive science, then, representations play a double role: they carry content and they cause behavior. Even though classical cognitive science and standard connectionism disagree about the actual format of representations, they share this much.¹

It is perhaps wise to make clear from the outset that we are not arguing against representations across the board. Instead, we are more interested in seeing how *far* one can go without invoking representational explanations. Our motto, then, is not “away with representations” but rather something like: “don’t use representations in explanation and modeling unless you really have to.” That is, we object to the widespread tendency within cognitive science to take representations as an unavoidable and unobjectionable starting-point. There are several reasons for our position in this, which we will outline briefly below.

First of all, in the context of planning, a representational account of imagined action leads one into the quicksand of the frame problem. Adequately representing all possibly relevant aspects of the situation and all possibly relevant consequences of actions quickly becomes computationally overwhelming (Haselager, 1997; McCarthy & Hayes, 1969; Pylyshyn, 1987). Thus, a system that should be capable of acting intelligently in the world soon is smothered by its own representational resources.

Secondly, the exact benefits of the available forms of representation has become a matter of heated argument. The classical view on representations, i.e., symbolic structures in a well-organized representational scheme (Fodor, 1975; Newell, 1980), is no longer universally endorsed within cognitive science. Since the rise of connectionism and the notion of distributed representation in the 1980s there has been an intense debate on what would constitute an efficient way of representing information. Both camps have indicated serious reasons to doubt the validity of the other camp’s representational scheme (e.g., Aizawa, 1997; Chalmers, 1993; Churchland, 1989; Fodor & Pylyshyn, 1981; Hadley, 1994; Haselager & van Rappard, 1998; Horgan & Tienson, 1997; Smolensky, 1988). We see the current widespread disagreement on what would constitute a viable form of representation as an indication of the fact that the representational foundation of cognitive science may not be all that rock-solid.

Finally, the response given to DST’s anti-representationalist claims (e.g., Van Gelder, 1995) by defenders of the representational position (Bechtel, 1998) makes clear that the meaning of the notion of representation has widened to such an extent that even simple mechanical devices (e.g., a steam-regulating device such as the Watt Governor) are considered to have representations. In our view, this makes it debatable whether the notion of representation has enough substance to play a useful role in the explanation of the causal mechanisms underlying truly cognitive systems (Haselager, de Groot, & van Rappard, submitted).

These considerations are, of course, far from being decisive. Still, we submit that they provide enough incentive to attempt to explain and model cognitive behavior without assuming representations from the start.

1.3. *Being representational without representations*

An explanation of cognitive capacity in representational terms is only valuable if, as Clark (1997) puts it, representations are usefully individuable. By this he means that the representation must be distinguishable as an entity serving a role as an information-carrier for

behavior. But what if, as DST would have it, a behavioral pattern is best understood as an emergent property of the overall activity of the system? Clark argues that

[a representation] will not be usefully individuable if (...) it somehow involves such temporally complex and reciprocally influential activity across so many subsystems that the “standing in” is best seen as an emergent property of the overall operation of the system. In such cases (if there are any), the overall system would rightly be said to represent its world—but it would not do so by trading in anything we could usefully treat as internal representations. (Clark, 1997, p. 168)

So, even if in some cases one could view a system *as a whole* as representing something, it does not follow that one needs to posit “stand ins” in the causal explanation of that particular behavior. If it can be shown that the system’s state is best seen as an *emergent property of the overall operation of the system*, a non-representational account seems the most natural way of analyzing the system. We submit that if imagined action can be fruitfully interpreted as an emergent property of the whole system, supposing an internal representation processing mechanism (representation in a causal–realistic sense of the term) is at best superfluous or at worst misleading.

The term “emergence” is not without problems. As Bechtel and Richardson (1993, p. 229) note, on the one hand the term is used too easily, applying to simple cases where the whole has properties not had by its components (e.g., a square has properties that its constituent line segments do not have). On the other hand, the term is used in relation to more interesting cases but *without* (or sometimes even instead of) a proper explanation of how the interaction of components is related to the emerging properties. In the present paper, we do not refer to emergent properties as properties of a system that has initially uncorrelated particles that become coordinated, such as the famous example of the Bénard cells (cf. Juarrero, 1999; Rosen, 1978; Thelen & Smith, 1994). Instead, we are interested in how different behaviors (i.e., the different judgments) emerge from the state the system (i.e., a participant) is in. Part of our interest in DST is derived from the fact that it provides the mathematical resources for a more solid interpretation of the notion of emergence (Haken, 1977, 1983; Haken & Wunderlin, 1990; Kelso, 1995).

1.4. Dynamical systems theory

Dynamic systems models typically describe behavior on the level of the whole system. On this account behavior is seen as a self-organized pattern, emerging from the interaction among subsystems. Such a pattern is called the collective variable or order parameter, which in turn can “enslave” the behavior of the components (cf. Haken & Wunderlin, 1990, p. 7; Kelso, 1995, pp. 8–9). Despite the great complexity at the level of the interacting components, the behavior of the system as a whole can be described in terms of low-dimensional order parameter dynamics. Differential equations can be used to describe the overall behavior of the system, and potential functions capture the long-term behavior of the dynamics underlying the system’s behavior. The potential function can be interpreted as describing an attractor landscape, in which the wells function as attractors and exemplify relatively stable states/modes of behavior. The attractor landscape may change and attractors can disappear or originate. As a consequence, transitions between different modes of behavior can be induced. The parameters that lead the system through these different behavioral patterns are called control parameters.

Although their name suggests otherwise, control parameters may be quite unspecific in nature, that is, in no sense do they *prescribe* the emerging pattern.

In a dynamic system, the order parameter is continuously defined, since all possible states are assumed to lie on a continuum referred to as state space. However, under the regime of a given order parameter it may be that only certain, more or less “discrete,” regions of the state space are stable. Even though transitions from one such “qualitative state” to another must theoretically involve a trajectory through all intermediate states, there is still only a limited set of states that can be maintained for long enough to sustain an overt judgment (in our model there are maximally two such regions of possible stability, “yes” and “no”).

The control parameters and order parameters governing dynamical systems are generally unknown. The key to studying a cognitive system then is to make the dynamics underlying the system’s behavior observable. One observable effect that is classically associated with dynamical systems is *hysteresis* (Case, Tuller, Ding, & Kelso, 1995; Gilmore, 1992; Kelso, 1995; Tuller et al., 1994).

Consider for example our experimental task. In some conditions (referred to as *coupled sequential runs*) rod-length will increase systematically to its maximum length and then decrease systematically to its minimum length. Hysteresis is the phenomenon observed when the transition from “no” to “yes” (i.e., the belief of participants regarding the possibility to reach the object) in the increase part of this coupled sequential run occurs at a larger rod-length than the transition from “yes” back to “no” in the decrease part of the run (see Fig. 1A). This effect reflects the fact that self-organized systems tend to hold on to the state that they reside in. Hysteresis can be one of the observable consequences of a system having several (instead of just one) relatively stable behavioral modes. The simultaneous existence of two or more attractors is called “multistability” because there is more than one stable state for the system to reside in. In the current context, this multistability means that the same rod can be judged as enabling or as not enabling successful reaching.

Another phenomenon that is ubiquitous to biological systems is *adaptation* (e.g., Helson, 1964; Parducci, 1965; Parducci & Wedell, 1986). Adaptation can be seen as having the effect of destabilizing the present state (desensitization), while stabilizing competing states (sensitization). Thus, adaptation leads to contrast, i.e., the tendency to give a different response than on the previous trial. Generally, adaptation is believed to be a function of both intensity and duration. Consider again our experimental task. If one is first handed a very long rod and subsequently is handed a much shorter rod, then one is less likely to judge the task as possible than if one was first handed a less long rod (this is the effect of intensity). Also, if one has judged the task as possible on many consecutive trials, one is more likely to switch judgment on the following trial (this is the effect of duration).

It is due to the effect of adaptation that another observable effect can be observed for multistable dynamical systems; viz., *enhanced contrast*. Enhanced contrast is the opposite of hysteresis and occurs when the two crossover points (at which the system changes to the other attractor) do not overlap but “underlap” (Fig. 1B). Finally, critical boundary is found when the change from one behavioral pattern to the other occurs at exactly the same point in the increase and decrease part of a coupled sequential run (Fig. 1C). It is assumed that critical boundary occurs when the effects causing hysteresis (i.e., tendency to cling to the present state) and enhanced contrast (i.e., adaptation) cancel each other out. In this study, we will use hysteresis,

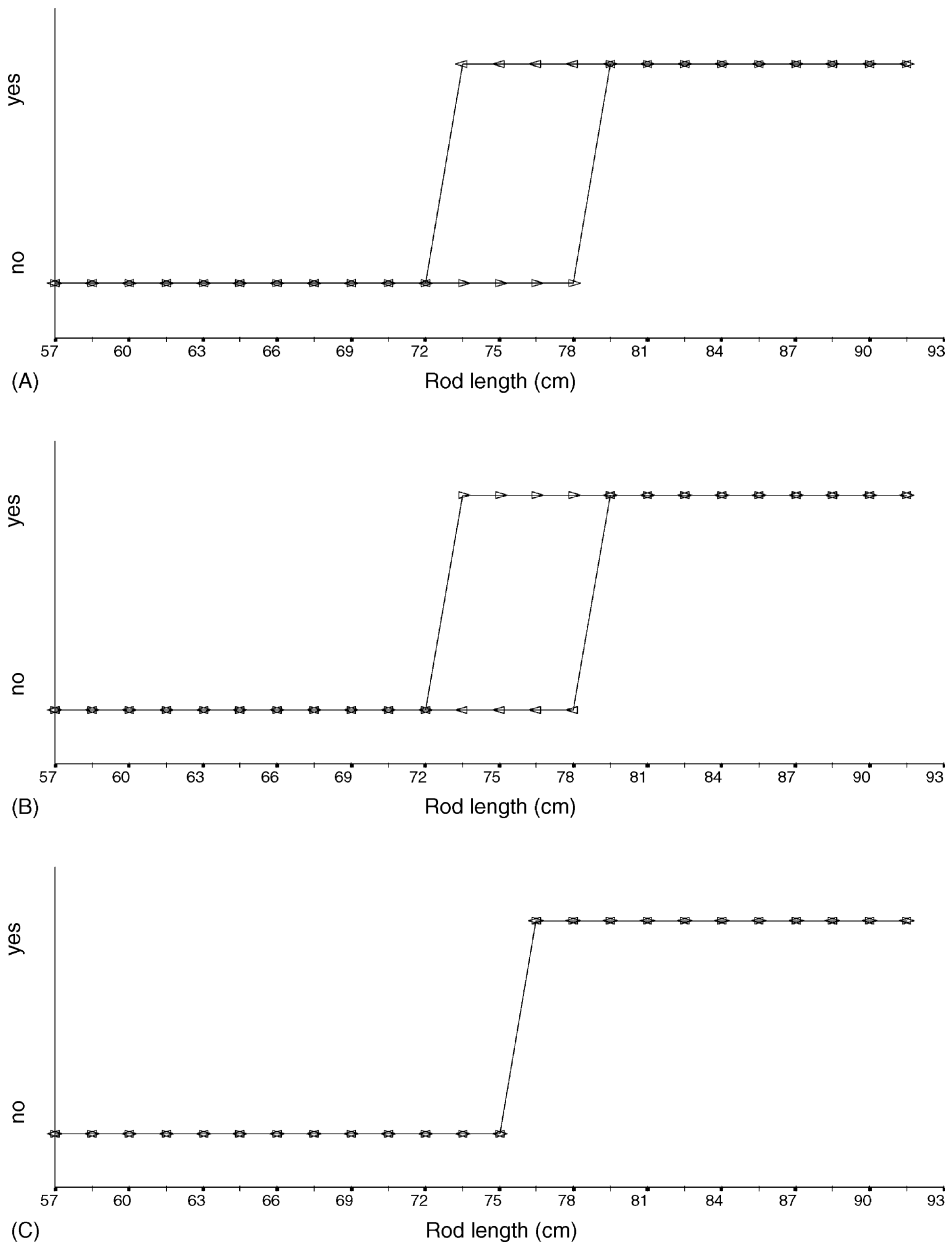


Fig. 1. Illustrations of (A) hysteresis, (B) enhanced contrast, and (C) critical boundary. Note that the transition in the hysteresis and enhanced contrast sequence is depicted at 3 cm of the critical boundary. The critical boundary and the size of the overlap are chosen for reasons of illustration and are not based on any theoretical or experimental considerations.

and its companion notions, enhanced contrast and critical boundary, as the empirical means to determine the dynamic nature of imagined action. Part of the attractiveness of dynamic models is derived from the fact that they can explain these three different effects by means of the *same* underlying mechanism of originating and decaying attractors.

1.5. Model description

Within the DST approach many different models have been developed to account for patterns of behavior. Given that the task we studied involved discerning which rods enabled successful reaching and which did not, we used a dynamical model to account for behavior with two attractor states. Tuller and colleagues (Case et al., 1995; Tuller et al., 1994) designed such a model for speech categorization phenomena. Following the example of Tuller et al. we used Eq. (1) to model our data.

$$V(x) = kx - \frac{1}{2}x^2 + \frac{1}{4}x^4,$$

(1)

in which $V(x)$, the collective variable of the system, represents a potential function with at most two minima which correspond to “no” (i.e., the participant indicates the belief or judgment that it is not possible to reach the object with the rod) and “yes” (the participant indicates the belief or judgment that it is possible to reach the object with the rod), respectively. The state the system is in regarding the imagined action is qualitatively denoted by x . The control parameter k specifies the direction and the degree of tilt of the potential function $V(x)$. As can be seen in Fig. 2, for $k = -1$, only one stable state exists in the system (i.e., “no”). Increasing k forces the function to tilt. Although the initial stable state continues to exist, the attractor becomes more shallow. When the control parameter reaches the critical value $-k_c$ an additional attractor becomes stable (“yes”). From this point on, until k reaches the second critical value, $+k_c$, the two stable states coexist (both “no” and “yes” are possible responses). When k reaches $+k_c$, the attractor corresponding to the first alternative ceases to exist. Increasing k further only deepens the remaining attractor.

In Tuller et al.’s model (as in all attractor models) it is assumed that the system’s state, x , changes over time under the influence of the attractor landscape. To incorporate the potential effects of random influences and noise inherent in the system, we assume that the trajectory can be thought of as a *random walk* (cf., e.g., Ratcliff & Rouder, 1998; Townsend & Ashby, 1983). There are many possible ways in which one can implement the specifics of such a random walk, but in general we assume that the mean drift² in the random walk at x is a function of $V'(x)$, such that the drift is *negative* for $V'(x) > 0$ and *positive* for $V'(x) < 0$. This means that the system

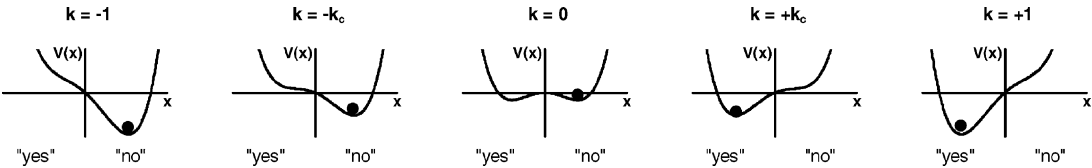


Fig. 2. Potential landscape defined by Eq. (1) for different values of k (after Tuller et al., 1994).

will tend to drift to the right on the x -axis for negative slope of the potential landscape and to the left for positive slope of the landscape. The characteristic nature of the attractor states for $V(x)$ is such that for all states within an attractor well the system will tend to be pulled towards the minimum of the well (see Fig. 2). Once the system is caught in an attractor well, the system will tend to drift towards the minimum (where $V'(x) = 0$), and then meander (stochastically) around this minimum. We say the system has *settled* when this situation occurs and assume that a decision (“yes” or “no”) is made, and a response initiated, as soon as the system has settled.

On each trial the system is assumed to start in some initial state, x_0 , and stochastically change over time until it settles and a response is initiated. This initial state, x_0 , can in theory lie anywhere on the x -axis, but it seems plausible to assume that after each trial the system will drift back to the neutral point, $x = 0$. Further, it also seems plausible to assume that this settling in the neutral point after a trial takes time, meaning that if the inter-trial interval (ITI) is relatively short, the initial state for the following trial will be biased by the final state of the system on the preceding trial. For example, if the response was “no” on the preceding trial (i.e., the system had settled in the “no”-attractor), then the initial state for the next trial will likely be $x_0 > 0$; provided, of course, that the ITI is short enough (see also Tuller et al., 1994, p. 8). If this next trial instantiates an attractor landscape that is multistable (e.g., $k = 0$), then the system will be more likely to settle in the “no”-attractor than had the initial state been $x_0 = 0$. As a result the model predicts an *assimilative bias*; i.e., all else being equal, responses on subsequent trials tend to be the *same*.

As mentioned before, in our experiment sometimes rod-length is systematically increased from minimum to maximum rod-length and subsequently systematically decreased from maximum back to minimum (ID-run), or vice versa (DI-run). If k would be a function of rod-length alone, then, due to the assimilative bias, the model would predict the hysteresis effect for DI- and ID-runs. This phenomenon is illustrated in Fig. 2. When k increases from -1 to $+1$, the little black ball (representing the system’s state) will tend to stay in the “no” attractor (depicted in Fig. 2). Conversely, when k decreases from $+1$ to -1 , the little black ball will tend to stay in the “yes” attractor. We will discuss now that k is assumed to be a function of more variables than rod-length alone, and explain how this allows the model to also predict an effect opposite to hysteresis, viz., enhanced contrast.

In the experiment, we manipulate the control parameter, k , by means of the independent variable, rod-length. Following Tuller et al. (1994) we assume that the relationship between the control parameter and the independent variable is not a one-to-one correspondence. Instead, we assume that k is a function of (1) rod-length, (2) the level of adaptation (which is a function of both repetitions, and length of rod on previous trial) and (3) random factors scaling the effect of (2) such as perceptual and cognitive characteristics of the participant. The relationship between the control parameter and rod-length can be symbolized by Eq. (2),³

$$k = \lambda + S((N_{\text{no}} - N_{\text{yes}}) - \lambda_{t-1}), \quad (2)$$

in which k specifies the value of the control parameter, λ , is linearly proportional to the length of the rod on the present trial (where $-1 \leq \lambda \leq +1$), λ_{t-1} is linearly proportional to the length of the rod on the preceding trial (where $-1 \leq \lambda_{t-1} \leq +1$), N_{no} is a growing function of the number of accumulative repetitions of “no” and N_{yes} is a growing function of the number

of accumulative repetitions of “yes.” $S \geq 0$ and represents relevant perceptual and cognitive characteristics of the participant that may fluctuate during the experiment.

In Eq. (2), two contrastive influences are incorporated: (a) adaptation as a function of the length (“intensity”) of the rod on the preceding trial; i.e., the longer the rod on the preceding trial the smaller k on the present trial (conversely, the shorter the rod on the preceding trial, the larger k on the present trial), and (b) adaptation as function of repetitions (“duration”) of a certain response; i.e., the more repetitions of “yes” the smaller k and conversely, the more repetitions of “no” the larger k .

We already mentioned that due to a tendency to cling to the state the system resides in (i.e., *local assimilation*) hysteresis can be observed in coupled sequential runs. However, if we take the contrastive influences of previous rod-length and repetitions into account the opposite effect, called *enhanced contrast*, can be observed as well.

Fig. 3 illustrates how the mechanism of Eq. (2) can lead to enhanced contrast in a coupled sequential run. In Fig. 3, the relation between the control parameter and the rod-length is illustrated for a coupled sequential run in which the rod-length first increases and then decreases (ID-run). For the sake of clarity, we hold S constant and only look at the effect of previous rod-length and accumulative responses. In an ID-run the participant is presented at first with the smallest rod (bottom left in Fig. 3), and thus, will start with responding “no.” With each next trial, the rod-length increments one step. With every next trial λ_{t-1} will become larger (i.e., less negative), but at the same time, N_{no} will become increasingly larger than N_{yes} (which will remain zero). Due to the fact that N_{no} grows increasingly larger than N_{yes} with every next trial, the increase in k will be larger than the increase in λ . When k reaches the value of $+k_c$ at the first transition point (left-hand side in Fig. 3), the participant switches to “yes”-responses. With every next trial N_{yes} will grow whereas N_{no} will remain constant. This will flatten the slope of the still increasing k . The increase sequence is followed by a decrease sequence, and at some point N_{yes} will start to outnumber N_{no} . In the initial part of the D-run this will cause the decrease in k to be larger than the decrease in λ , resulting in a steep slope downwards (right-hand side in Fig. 3). When $-k_c$ is reached again a transition occurs and the participant will switch to no-responses again. Thus, Fig. 3 illustrates that for some $S > 0$, the transition

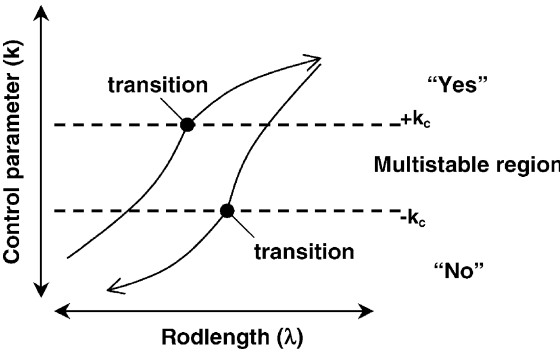


Fig. 3. Illustration of the relationship between the control parameter and rod-length, for fixed $S > 0$, in a coupled sequential run in which rod-length first increases and subsequently decreases (see text for details).

from “yes” to “no” occurs at a larger rod-length than the transition from “no” to “yes”; an example of the *enhanced contrast* effect.

One can imagine that for certain settings of the parameters one may find that the first and second transition occur at exactly the same rod-length. This *critical boundary* effect is relatively rare, because the number of parameter settings that result in it is much smaller than the number of parameter settings that lead to either hysteresis or enhanced contrast.

According to the attractor model that we present a response on trial t can be different from the response on trial $t - 1$ for two reasons: (1) a transition has been induced by the change in the control parameter k , or (2) a transition has occurred due to *random* influences (i.e., the evolutionary trajectory is a *random walk*). If k is, say, systematically increased from some value smaller than $-k_c$ to some value larger than $+k_c$ then always at least one transition from “no” to “yes” will always occur. A transition will either occur at $+k_c$ (i.e., a type-1 transition) or before $+k_c$ (i.e., a type-2 transition). It is of course possible that more than one type-2 transition occurs before $+k_c$ is reached (e.g., for consecutive trials, each instantiating a multistable system, it is possible to observe the response sequence: “no–yes–no–yes–. . .”). Since, the possibility for a type-2 transition is present for every trial that instantiates a multistable system, the probability of observing at least one type-2 transition is larger if many consecutive trials instantiate multistable systems.

We call the number of consecutive trials that each instantiate a multistable region the *width* of the multistable region for a given sequence of trials (with sequence, here, we mean that either k systematically increases or systematically decreases over trials). Note that the model makes a prediction about under what conditions a wide or narrow multistable region will be expected. Namely, as illustrated in Fig. 3, the *contrastive influence* of repetitions of the same response is such that it *narrows* the multistable region in a sequence. In our analyses, we use two measures of the width of the multistable region to test this prediction. First, we use the number of switches observed in a given sequence as an index of the width of the multistable region (note: in a narrower multistable region there will be less room for type-2 transitions). As a second measure of the width of the multistable region we use the difference between the longest rod inducing a “no”-response and the shortest rod inducing a “yes”-response within a given sequence. This difference should be larger for a wider range of multistability than for a narrower range of multistability.

2. Model predictions

We summarize the predictions that can be derived from the model for our experimental task. Before discussing these predictions, we wish to clarify the distinction between assimilation and hysteresis and the distinction between contrast and enhanced contrast, as we will use these terms throughout the discussion of our results.

In the present context, contrast and assimilation are *locally* defined effects, i.e., defined at the level of individual trials: (1) contrast is the tendency to give a different response on the present trial than on the previous trial, while (2) assimilation is the tendency to give the same response on the present trial as on the previous trial. We hypothesize that contrast is a result of adaptation while assimilation is a result of a system’s resistance to change (i.e., stability).

Thus, both adaptation and resistance to change are assumed to be continuously operational in any cognitive system.

Enhanced contrast and hysteresis, on the other hand, are more globally defined, i.e., defined at the level of coupled sequential runs (i.e., increase–decrease [ID-runs] and decrease–increase [DI-runs]): (1) enhanced contrast is the effect when the switch from “no” to “yes” occurs for a shorter rod-length than the switch back from “yes” to “no,” while (2) hysteresis is the effect when the switch from “no” to “yes” occurs for a longer rod-length than the switch back from “yes” to “no.” Enhanced contrast and hysteresis can be thought of as resulting from the amplification of local contrast and local assimilation in the location of the 50% point on the rod-length continuum in coupled sequential runs.

The interrelationship between Eqs. (1) and (2) as described above leads to the following predictions for our experiment:

- (1) There is a tendency in the dynamic system to remain in the state it resides in due to the biasing effect of the final state of the preceding trial on the initial state for the present trial. Thus, the model predicts an assimilative bias. This assimilative bias can be tested in random sequences by inspecting the conditional probability of a “yes” or “no” response on the present trial given a “yes” or “no” response on the preceding trial.
- (2) Accumulative repetitions of “yes” and the presentation of “long rods” are assumed to cause the multistable region to shift towards the upper end of the rod-length continuum (i.e., to longer rods). Conversely, accumulative repetitions of “no” and “short rods” are assumed to cause the multistable region to shift towards the lower end of the rod-length continuum. Thus, the model predicts that the 50% point in a random sequence with overall less “no” (more “yes”) responses should be lower (i.e., corresponding to a shorter rod-length) than the 50% in a sequence with overall more “no” (less “yes”) responses (we use the factor *Range*, discussed in Section 3, to test this prediction). The contrastive effect of the previous rod-length can also be tested in random sequences by inspecting the predictive power of rod-length on the preceding trial on judgment on the following trial. In particular, the model predicts an inverse relationship between rod-length on the previous trial and the probability of a “yes”-response on the present trial.
- (3) The model predicts both hysteresis and enhanced contrast (and in rare cases, critical boundary as well). Although the finding of both patterns supports the model, it does not provide a strong test. To have a strong test of the model we have to test the *relative frequency* of these effects under conditions predicted by the model to affect this relative frequency. For example, the model predicts that the higher the number of repetitions of “yes” in ID-runs, where rod-length systematically increases and subsequently systematically decreases (or of “no” in DI-runs) the greater the chance of observing enhanced contrast and the smaller the chance of observing hysteresis. Conversely, the smaller the number of repetitions of “yes” in ID-runs (or of “no” in DI-runs) the greater the chance of observing hysteresis and the smaller the chance of observing enhanced contrast. In addition, the model predicts that observations of critical boundary will overall be very limited. We test these predictions by inspecting the relative frequency with which hysteresis, enhanced contrast and critical boundary occur in coupled sequential runs.

- (4) Within the multistable region switches in judgment can occur as a consequence of random disturbances. The narrower the multistable region gets (e.g., due to repetitions of a certain response—see Fig. 3) the smaller the chance of observing switches of the judgment. Also, the narrower the multistable region gets the smaller the difference between the maximum rod-length for which a “no”-response is observed (Max_{no}) and the minimum rod-length for which a “yes”-response is observed (Min_{yes}).

3. Method

3.1. Participants

Five males and nine females, participated in the experiment. All but two female participants were right-handed. The age of 13 participants ranged from 22 to 28 years. One male participant was significantly older than the rest, viz., 56 years. The height of participants ranged from 1.56 to 1.88 m, with an average of 1.76 m. The average arm length was 0.59 m, with a range of 0.49–0.67 m. All participants volunteered to participate. All but one, who did not want to be rewarded, were paid for their participation or participated as a means to fulfilling a course requirement.

3.2. Materials

Rods with a diameter of 1.25 cm were used, ranging in length from 57.0 to 91.5 cm, in 1.5 cm increments.⁴ The 24 rods were constructed from wood (density 0.67 g/cm³). Attached to each rod was a handle of identical material with the length of 11.5 cm and a diameter of 1.25 cm. A small disc divided the handle from the rod.

A 50 g PVC cylinder (diameter 5 cm, height 6 cm) was placed on a table (25 cm × 25 cm). The height of the table was adjusted to the participant's wrist height with the arm at the side. The back of the cylinder was placed against a panel of 12.5 cm height and the front of the cylinder was aligned with the front edge of the table.

3.3. Design

Each participant performed the judgment task under several conditions. There were three kinds of *sequences* in which rods were given to the participant, namely (1) increase sequences (I): rod-length increased from minimum to maximum in 1.5 cm increments; (2) decrease sequences (D): rod-length decreased from maximum to minimum in 1.5 cm increments; (3) random sequences (R): the rods ranging in length from the minimum to maximum were randomly assigned to the task. The two sequential conditions (1) and (2) were always coupled, resulting in two kinds of coupled sequential runs: ID- and DI-runs. Coupled sequential runs were always followed by a random sequence (3), resulting in two possible blocks of runs, namely increase–decrease–random (IDR) blocks and decrease–increase–random (DIR) blocks. The random sequence served as a kind of buffer between the coupled sequential runs, and as the condition in which to test for local assimilative and contrastive effects.

For the rods two different ranges were used in the experiment, namely Range 1 of 57.0–85.5 cm and Range 2 of 63.0–91.5 cm. Thus, there were two possible minima and maxima for the three sequences described above. Within a given block, the minimum and maximum for the three constitutive sequences (I, D and R) were the same.

The four possible combinations of block and range in the experiment were thus IDR-1, IDR-2, DIR-1 and DIR-2. Each of these combinations occurred twice in one experimental session, resulting in a total of 480 trials ($2 \text{ ranges} \times 2 \text{ blocks} \times 3 \text{ sequences} \times 20 \text{ rods} \times 2 \text{ repeated measures}$) per participant. The block-range combinations were randomized within an experimental session, with the constraint that each block-range combination appeared as often in the first half of a session as in the second half.

3.4. Procedure

A participant was asked to bend forward, with the preferred arm stretching forward, as far as possible (maintaining enough balance to stay flat on the feet). The distance between the feet and the hand in this position was measured. Then the participant was asked to leave the experimental room. To determine the place at which a participant had to make the judgment we added 75 cm to the participants' maximum reaching distance as measured. This place was demarcated on the floor. The participant stayed at this place, in a normal, upright position, during the entire experiment. Note that 75 cm is the median of the range of rod-lengths used. Hence, for all participants approximately half of the rods would enable reaching, and half would not.

While standing at the demarcated place it was explained to the participant that the goal was to judge whether the cylinder on the table could be displaced with the tip of the rod from this place while keeping the two feet flat on the floor. From behind a curtain an experimenter handed a rod to the participant (i.e., during a trial participants had full vision of the rod but participants had no idea about how the rods related to each other). The instruction was to hold the rod so that it made an angle of approximately 45° upwards with the horizontal. Participants stood upright at the demarcated place with the rod in one hand and reported whether they thought they were able to displace the cylinder with a simple “yes” or “no”. After a participant had given the categorical judgment the rod was returned to the experimenter who handed the participant a new rod for which the participant again made a judgment. To ensure that the perceptual effect of the previous trial would be carried over to the following trial, we tried to minimize the ITI as much as possible. No feedback regarding accuracy was given. One experimental session lasted approximately 1 h, including a short break after participants had completed half of the trials.

4. Results

Most participants showed a transition in the judgment (reachable or not) in all sequences (increase-, decrease- and random-sequences), that is, for 9 of the 14 participants at least 1 switch from “yes” to “no” (or vice versa) occurred across the rod-length continuum, in all 24 sequences. For three additional participants such a transition occurred in 22, 20 and 18

sequences, respectively. All these 12 participants switched at least once between the two judgments in all random sequences. The two remaining participants, however, did not. One of these participants (Participant 6) categorized all rods as enabling successful reaching for the cylinder, thus, producing a yes-response for all 480 trials. For the other participant (Participant 13) a transition occurred in only three sequences (one in a random sequence, one in a increase sequence, and one in a decrease sequence). It seems that these two participants overestimated the distance reachable with the rods so much that the lower-end of the range (57.0 cm) was still too high to evoke a perceptual transition. Because this led to little or no variation in responses, these participants' data were excluded from the analyses.

Plotting the probability of a “yes”-response against rod-length for the remaining 12 participants for the three types of sequences resulted in the distributions as depicted in Fig. 4. The figure illustrates an effect of type of sequence. The rod receiving a yes-response 50% of the time was on average smaller in increase sequences (viz., ± 66.0 cm) than in the decrease sequences (± 70.5 cm). This difference is indicative of an overall *enhanced contrast* effect (see also, Fitzpatrick, Carello, Schmidt, & Corey, 1994). Further, Fig. 4 shows that the length for which there was a 50% point in random sequences (viz., ± 67.5 cm) lies between the two 50% points of the increase- and decrease-sequences. Note that some smaller rods (i.e., rods ranging in length from 60.0 to 64.5 cm) were on average more often categorized as enabling successful reaching in the two sequential runs than in the random runs. Some participants whose personal 50% category boundary fell on the lower-end of the parameter continuum caused this divergence.

Finally, participants in this experiment tended to *overestimate* their reaching distance. Given the individually defined distance to table (personal maximum reaching distance without rod + 75 cm) the *expected* 50% category boundary would be about 75 cm for all participants. The *observed* 50% category boundaries for the three experimental condition depicted in Fig. 4 are all lower than this.

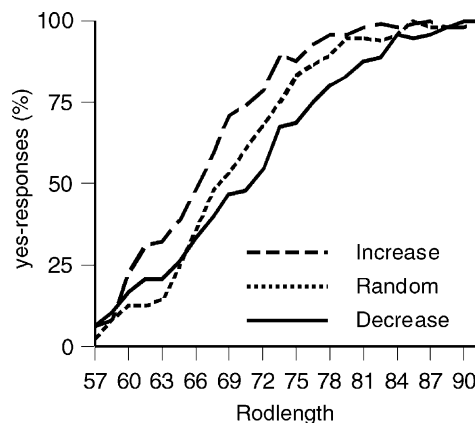


Fig. 4. Percentage of “yes”-responses, averaged over participants, per rod-length for increase, random and decrease sequences separately.

4.1. *Effects of sequence and range*

To test the effect of sequence, suggested in Fig. 4, as well as a possible effect of range, a direct logistic regression analysis was performed on the judgments (“yes” or “no”) for each participant separately. Length (ranging from 57.0 to 91.5 cm) was entered as a continuous predictor, and Sequence (increase, decrease and random) and Range (Range 1: from 57.0 to 85.5 cm, Range 2: from 63.0 to 91.5 cm) as categorical predictors. Given that all predictors were entered simultaneously the variance accounted for by each is unique. Table 1 summarizes for each participant the found β , and its significance level, for each predictor (we will denote the mean β , as averaged over participants, by B).

Participants’ tendency to overestimate was captured by a large negative constant for all participants ($B = -36.02$, $SE = 2.27$). Not surprisingly, also Length was a significant predictor for all participants; i.e., the probability of “yes”-response increased with increasing length ($B = 1.34$, $SE = 0.04$). More importantly, we found that Sequence was a significant predictor for most participants. Overall, the increase condition was associated with a higher probability of “yes” ($B = 1.34$, $SE = 0.23$), and the decrease condition was associated with a lower probability of “yes” ($B = -0.63$, $SE = 0.42$), as compared to the random condition. A paired-samples t -test showed that β was on average larger in the increase condition than in the decrease condition, $t(11) = 4.04$, $p < .01$ (hence, the overall “enhanced contrast” effect in Fig. 4). Note, however, that at the individual level this contrastive effect was not significant for five participants, and for two participants (7 and 10) the effect of sequence was even in the opposite direction. Also, though Range did not add significantly to the predictive power of the regression model at the individual level, its β was on average larger than zero ($B = 0.58$, $SE = 0.20$), $t(11) = 2.97$, $p < .05$, indicating that on average the probability of “yes” was lower in Range 2 as compared to Range 1 (i.e., when controlling for the effect of Length). This effect of Range can be interpreted as being due to the contrastive influence of having overall more “yes”-responses in Range 2 (consisting of more long rods) than in Range 1.

4.2. *Local assimilative and contrastive effects*

To test whether local contrastive or assimilative effects were present a logistic regression was run on judgment (“yes” or “no”) in random sequences for each participant separately. To test for assimilation, the response on the previous trial (Previous Response) was entered as a categorical predictor. To test for an effect of adaptation level, the length of the rod on the previous trial (Previous Length) was entered as a continuous predictor. To ensure that the predictive value of Previous Response and Previous Length could not be attributed to correlation between these variables and rod-length or range, Length (continuous) and Range (categorical) were simultaneously entered in the logistic regression as well. Table 2 shows the found β weights for Previous Response and Previous Length, and their significance level, for each participant.

Based on the assumption that a dynamical system will tend to remain in the attractor it is in, one expects participants to tend to give the same response on the present trial as they did on the previous trial. In accordance with this prediction, we found a positive weight for Previous Response in the regression analysis ($B = 1.71$, $MS_e = 0.84$), which was on average

Table 1
Beta weights (β) obtained in a direct logistic regression on judgment, with Length, Sequence and Range as predictors, and the significance level of each weight

Participant	Constant		Length		Increase		Decrease		Range 1	
	β	Significance	β	Significance	β	Significance	β	Significance	β	Significance
1	−27.63	**	0.42	**	0.47	n.s.	−1.13	*	−0.04	n.s.
2	−29.79	**	0.39	**	0.88	*	−1.93	**	0.61	+
3	−50.49	**	0.75	**	0.87	n.s.	−2.28	**	−0.14	n.s.
4	−47.00	**	0.66	**	1.48	**	−1.60	**	0.41	n.s.
5	−34.54	**	0.49	**	1.41	**	−0.56	n.s.	0.10	n.s.
7	−43.16	**	0.70	**	1.58	*	2.04	**	1.89	*
8	−32.60	**	0.45	**	0.42	n.s.	−1.01	*	−0.35	n.s.
9	−29.44	**	0.36	**	1.64	**	−0.47	n.s.	0.42	n.s.
10	−28.07	**	0.43	**	0.29	n.s.	0.59	n.s.	1.50	**
11	−29.64	**	0.46	**	2.02	**	0.38	n.s.	0.47	n.s.
12	−39.56	**	0.64	**	1.97	**	0.79	n.s.	1.04	n.s.
14	−40.34	**	0.56	**	3.06	**	−3.14	**	1.09	*
Average (<i>B</i>)	−36.02		0.53		1.34		−0.69		0.58	

Note: (**) means $p < .01$, (*) $p < .05$, (+) $p < .10$, and (n.s.) means $p \geq .10$.

Table 2
Beta weights (β), and their significance, for Previous Length and Previous Response, obtained in a direct logistic regression on judgment, with Previous Length, Previous Response, Length and Range as predictors

Participant	Previous Response		Previous Length	
	β	Significance	β	Significance
1	1.88	n.s.	−0.07	n.s.
2	1.86	n.s.	−0.11	n.s.
3	0.42	n.s.	−0.02	n.s.
4	1.89	+	−0.12	+
5	1.11	n.s.	−0.07	n.s.
7	1.54	n.s.	−0.04	n.s.
8	1.81	n.s.	−0.12	+
9	2.61	*	−0.04	n.s.
10	1.97	+	−0.09	+
11	3.00	+	−0.14	*
12	2.42	+	−0.09	n.s.
14	0.06	n.s.	−0.10	n.s.
Average (<i>B</i>)	1.71		−0.08	

Note: (*) means $p < .05$, (+) $p < .10$, and (n.s.) means $p \geq .10$.

significantly larger than zero, $t(11) = 7.00$, $p < .001$. This assimilative bias was (marginally) significant at the individual level for 5 of the 12 participants, and at least directionally presented for all participants (i.e., all $\beta > 0$). On the assumption that adaptation induces a contrastive effect, one expects that the tendency to respond “yes” on a given trial is larger when the rod on the previous trial was small, than when it was large. In accordance with this prediction, we found a negative weight for Previous Length in the regression analysis ($B = -0.08$, $MS_e = 0.04$), which was on average significantly smaller than zero, $t(11) = 7.87$, $p < .001$. The contrastive effect of previous rod-length was (marginally) significant at the individual level for 4 of the 12 participants, and at least directionally presented for all participants (i.e., all $\beta < 0$).

4.3. Response patterns in coupled sequential runs

To investigate the relative frequency of hysteresis, critical boundary and enhanced contrast in coupled sequential runs a measure was required for the transition point in each increase and decrease sequence independently. In 36 of the 192 sequential runs multiple transitions were observed across the rod-length continuum. Given that we interpret such additional switches as a result of random influences that cause the system to jump from one attractor to another, the boundary of the multistable region is best estimated by the rod-length for which the *last* switch occurred within a given sequence. In an increase sequence this *last switch point* was defined as being in between the longest rod receiving a no-response and the subsequent rod. Conversely, in a decrease sequence the last switch point would be in between the shortest rod receiving a yes-response and its subsequent rod.

Each coupled sequential run (ID- and DI-runs) was coded for the type of response pattern it showed. If the last switch point marked a shorter rod in the increase-sequence of a

Table 3

Number of coupled sequential runs (out of total of eight) that resulted in either enhanced contrast, critical boundary or hysteresis per participant

Subject	Enhanced contrast	Critical boundary	Hysteresis
1	6	1	1
2	5	1	2
3	8	0	0
4	8	0	0
5	6	1	1
7	1	1	3
8	7	0	1
9	6	0	2
10	2	0	6
11	4	1	3
12	4	1	1
14	8	0	0

Note: Three coupled sequential runs for Participant 7 and two coupled sequential runs for Participant 12 could not be coded as enhanced contrast, critical boundary or hysteresis, because no perceptual transition occurred in those runs.

coupled run than in the decrease-sequence an *enhanced contrast* effect was coded. On the other hand, *hysteresis* was coded if the rod for which the last switch occurred was longer in the increase-sequence than in the decrease-sequence of a coupled run. A *critical boundary* was coded when the last switch points were exactly the same for the two parts of a coupled sequential run. The distribution of the three possible response patterns over participants is depicted in Table 3. Five coupled sequential runs were excluded from the analyses because no perceptual transition occurred. These were two runs for Participant 12 and three runs for Participant 7 (see also Table 1). Of the total 91 remaining sequential coupled runs, 66 runs (72.8%) showed an enhanced contrast effect and 20 runs (20.7%) showed a hysteresis effect (the relative frequency of hysteresis and enhanced contrast that we observed across coupled sequential runs is comparable to what Fitzpatrick, Carello, Schmidt, & Corey, 1994 observed across participants). Critical boundary occurred in only six sequential coupled runs (6.5%), and no more than once per participant.

4.4. Interaction of response pattern with order of coupled sequences

Because participants tended to overestimate the distance reachable, more “yes”- than “no”-responses were given. As a consequence, the number of accumulative repetitions of “yes” in a ID-run were, on average, larger than the accumulative repetitions of “no” in a DI-run. Hence, the dynamical model predicts that the chance of observing enhanced contrast is greater, and the chance of hysteresis is smaller, in ID- than in DI-runs.

An analysis of the frequencies of the two response patterns confirmed this prediction. A Pearson χ^2 -test with SequenceCoupling (ID-, DI-runs), and ResponsePattern (enhanced contrast, hysteresis) indicated a significant association between SequenceCoupling and ResponsePattern, $\chi^2(1) = 4.44$, $p = .035$. Enhanced contrast occurred more frequently

in ID-runs (37 times) than in DI-runs (29 times). Hysteresis on the other hand occurred more frequently in DI-runs (14 times) than in ID-runs (6 times). Critical boundary occurred as often in ID-runs (3 times) as in DI-runs (3 times).

4.5. Switches as a measure of multistability

As mentioned before, additional switches (i.e., alternating yes- and no-responses on successive trials preceding the last switch point) were observed for some participants in some sequential runs. Such additional switches occurred on 88 of the 3574 trials in sequential runs. Note that the number 3574 represents the total number of trials, 3840, *minus* the first trial of each coupled sequential run and *minus* the trials in which a last switch point was observed. The first trial was excluded because the trial preceding that trial was part of a random run (thus, a switch on that trial would not be informative), and the last switch point was excluded because only the switches that occur *in addition* to the last switch point are of interest here (i.e., those switches that are brought about solely by random influences).

Two estimates of the size of the multistable region can be defined: (1) the *number* of additional switches, and (2) the difference between the length of the longest rod eliciting a no-response and the length of the shortest rod eliciting a yes-response (*plus* 1.5 cm to correct for the increment size). We report analyses for both these estimates to test whether the width of the multistable region is affected by repetitions as predicted by our model.

On average $|(N_{\text{no}} - N_{\text{yes}})S|$ gets larger in the second than in the first half of a coupled sequential run. Because this increases the pace of change of k , this causes the multistable region to be smaller in the second half of a coupled sequential run than in the first half. In a smaller multistable region, there is less room for additional switches. Therefore, we hypothesized that the number of additional switches would be larger in the first than in the second half of coupled sequential runs. A Pearson χ^2 -test of association performed on the switches and non-switches (excluding the first trial of each coupled sequential run and the trials on which a last switch point was observed), for RunHalf (first half, second half of a coupled sequential run), showed that indeed significantly more additional switches occurred in the first half of a coupled sequential run (54 times) than in the second half (34 times), $\chi^2(1) = 5.81$, $p < .05$.⁵ This effect of RunHalf was more prominent in decrease sequences (34 vs. 19 in first and second RunHalf, respectively) than in increase sequences (20 vs. 15 in first and second RunHalf, respectively), which can be attributed to the fact that $|(N_{\text{no}} - N_{\text{yes}})S|$ becomes much larger in decrease sequences in ID-runs than in increase sequences in DI-runs, due to the fact that participants overestimated their reaching distance to a large degree.

Also, we found that more additional switches occurred in Range 1 (61 times) than in Range 2 (27 times; $\chi^2 = 13.70$, $p < .001$). Interestingly, this effect of range was observable for both increase and decrease sequences (see Fig. 5).

The effect of range in decrease sequences can again be explained in terms of the relatively large number of accumulative repetitions of “yes” in D-runs due to the fact that participants overestimated their reaching distance. The effect of range in increase runs, however, is consistent with the two-attractor model as well. Namely, as can be seen in Fig. 4, even the shortest rods used in the experiment were occasionally judged to enable successful reaching. Further, the shortest rod in Range 2 (i.e., 63.0 cm) was judged as enabling successful

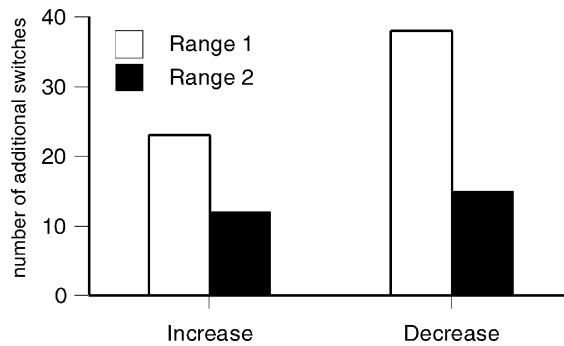


Fig. 5. Number of additional switches observed in Range 1 and Range 2 for increase and decrease sequences separately.

reaching once by two participants, and as enabling successful reaching even 50% of the time by three participants. This means that the left boundary of the multistable region was not only on average closer to the left end of the range of rod-lengths (i.e., shorter rods) but even outside Range 2 for a considerable number of participants. Thus, for these participants, the increase sequences in Range 2 started well within the multistable region. Consequently there were simply fewer opportunities for switching in increase sequences in Range 2 as compared to Range 1, which explains the low frequency of additional switches in Range 2 for increase sequences.

A second estimate of the size of the multistable region is provided by the difference between the maximum rod-length inducing a no-response (Max_{no}) and the minimum rod-length inducing a yes-response (Min_{yes}), plus 1.5 to correct for the size of the increment. If only one switch in judgment occurs in a given sequence then this estimate is zero. When at least two switches occur in a given sequence then this estimate would be larger than zero, but the actual size would depend on where on the rod-length continuum the “first” and “last” switch occurred. We computed $(\text{Max}_{\text{no}} - \text{Min}_{\text{yes}} + 1.5)$ for all participants for all Sequence \times Range \times RunHalf. A randomization test⁶ was performed to test for main effects and interactions.

Although, the mean size of the multistable region, as estimated by $(\text{Max}_{\text{no}} - \text{Min}_{\text{yes}} + 1.5)$, was found to be smaller in the second half ($M = 0.130$, $SD = 0.23$) than in the first half of coupled sequential runs ($M = 0.234$, $SD = 0.44$), this difference was not significant ($p = .26$). The main effect of Range was found to be marginally significant ($p < .10$) indicating that the width of the multistable region, as estimated by $(\text{Max}_{\text{no}} - \text{Min}_{\text{yes}} + 1.5)$, tended to be larger in Range 1 ($M = 0.242$, $SD = 0.43$) than in Range 2 ($M = 0.122$, $SD = 0.24$). No interaction between Range and Sequence was found ($p > .50$), indicating that the effect of Range was similar for increase and decrease sequences (though, *theoretically* the effect of range in decrease sequences is distinct from the effect of range in increase sequences—see earlier comments on the analysis of “additional switches”). In sum, the analyses on the two estimates of the size of the multistable region give a very similar picture; the width of the multistable region seems to be modulated by accumulated repetitions.

5. Discussion

Clark (1997) challenged DST to explain behavioral phenomena that are considered to be “representation-hungry” cases. We took up this challenge by examining to what extent a dynamical model could account for participants’ reports about the predicted outcome of an imagined action. The patterns of responses by participants were found to be in close agreement with the predictions of a two-attractor model (Tuller et al., 1994).

First, it was found that in random sequences participants tended to give the same categorical judgment as on preceding trials. This *assimilative* effect is in accordance with the notion that a dynamical system tends to cling to the state it resides in (*Prediction 1*). Further, we observed an inverse relationship between previous rod-length and probability of a “yes”-response, indicating that the rod-length on a preceding trial had a *contrastive* effect. Also, we found that on average the transition occurred at a shorter rod-length in Range 1 than in Range 2—an effect that is consistent with the assumption that response repetitions have a contrastive effect (*Prediction 2*).

In coupled sequential runs (ID- and DI-runs) we observed all three effects that are predicted by the model, viz., hysteresis, critical boundary, and enhanced contrast. As expected, critical boundary was the rarest of the three. Because participants overestimated their reaching distance to a large degree, much more accumulative repetitions of “yes”-responses occurred in coupled sequential runs in which rod-length first increased and subsequently decreased (ID-runs) than “no”-responses occurred in runs in which rod-length first decreased and then increased (DI-runs). As predicted, enhanced contrast occurred more often, and conversely hysteresis less often, in ID-runs as compared to DI-runs (*Prediction 3*).

Finally, more additional switches (alternating “no”- and “yes”-responses) were observed when the multistable region was expected to be relatively large, than when it was expected to be relatively small (*Prediction 4*). That is, more additional switches were observed in the first part of a coupled sequential run (i.e., I in ID, and D in DI) as compared to the second part of a coupled sequential run (i.e., D in ID and I in DI). Also, more additional switches were observed in Range 1 as compared to Range 2. We found similar effects when the width of the multistable regions was estimated by the difference between the longest rod leading to a no-response and the smallest rod leading to a yes-response.

In sum, a simple dynamical model suffices to account for our experimental findings. The pattern of results can be usefully described as a consequence of the interrelationship between the control parameter k and the collective variable $V(x)$ governing the system. In accordance with the general DST perspective, the collective variable is assumed to be a non-reducible description of the task-specific system. That is, the collective variable is not seen as the result of a transformation or synthesis of representational units. Instead, this “imaging landscape” is thought of as an *emergent property* of the system as a whole. Thus, even though the system as a whole can be viewed as representing the (possibility of) imagined action, the attractor model does not postulate internal representations in order to account for this capacity.

Before discussing the consequences of these results for Clark’s representation-hungry challenge, we will examine the relation between our results and other experimental findings. The finding that participants tended to overestimate the distance reachable is in correspondence with the general finding in other experiments that participants without using tools tend to

overestimate their reaching distance (e.g., Carello et al., 1989; Heft, 1993; Robinovitch, 1998; Rochat & Wraga, 1997). As we noted in our discussion of the nature of our task, Heft (1993) indicates that the overestimation of the reaching distance reflects the interaction of higher cognitive processes with perceptual processes. Hence, the fact that we find overestimation indicates that higher cognitive processes play a role in our experiment as well. Thus, this finding further corroborates our suggestion that our task can be used as a representation-hungry case.

Furthermore, our results are comparable to the results of experiments of Fitzpatrick et al. (1994) in which participants were allowed to inspect a slope either visually or haptically (i.e., by probing with a rod). Participants had to judge whether a slanted surface afforded upright stance when both visual and haptic information was available without actually standing on that surface. Fitzpatrick et al. (1994) also found enhanced contrast and hysteresis effects at the level of the individual participants. This indicates that the dynamical model we applied to our task might be more generally applicable to different cases of simple imagination.

Although our main aim here merely is to show that a dynamical account of imagined action is *possible*, we will try to indicate briefly why a dynamical account might even be thought to be preferable to a representational account. In accordance with the general DST perspective, our model assumes that all dynamical systems tend to hold on to the state they reside in, and that hysteresis follows directly from the organization of the system. Enhanced contrast can be understood as arising from the effect of adaptation on the control parameter (which in turn modulates the emerging behavioral pattern of the dynamical system). Thus, by means of the *same* model *both* hysteresis and enhanced contrast can be accounted for. Although there may be representational explanations for each phenomenon (hysteresis, enhanced contrast, critical boundary) *separately*, we fail to see a unified representational explanation for them taken together.

Consider how a possible representational account would fare with respect to hysteresis. One could argue that the representations underlying the judgment are more active or more accessible when they have just been accessed (e.g., residual-activation, facilitative priming, etc.). In effect this would cause the representational system to “tend to hold on to” prior used representations, leading to an assimilative effect. This type of explanation, however plausible, has a problem when it needs to account for the occurrence of enhanced contrast as well. To explain the contrast effect one could argue for some mechanism that causes the representations underlying the judgment to be less active, or less accessible when those same representations have just been accessed (e.g., repetition blindness, deactivation or inhibition). In effect this will cause the representational system to be more sensitive to the difference between a current situation and the one just encountered, leading to a contrastive effect. The problem, however is that the two representational explanations of hysteresis and enhanced contrast seem to be hard to integrate (if not mutually exclusive). Moreover, it is not clear how the two mechanisms would give rise to the *systematicity* in the occurrence of hysteresis and enhanced contrast that we observed in the experiment and that follow from the dynamical model in a straightforward way.

Finally, and perhaps most speculatively, we would like to question once again the “intuitive desire” for a representational explanation. Perhaps one could come up with one, along the lines we indicate above or otherwise. But *why* would one want to if there is an alternative and simpler account available? The motto; “don’t use representations in explanation and modeling unless

you really have to” can be understood as an instantiation of Occam’s razor. Representations form an additional assumption in an account of observable behavior, and this assumption is not entirely without problems, as can be seen from the widespread disagreements about their exact nature, and the computational problems surrounding their efficient storage and usage.

One of the underlying reasons for wanting a representational explanation may be the idea that representational models provide a mechanism whereas dynamical accounts such as the one we give above merely are convenient ways of describing the data. However, we think this suggestion reflects a tendency within cognitive science to equate “mechanism” with “representational–computational account.” In our view, *both* representational and dynamical models provide a mechanism in the sense that they both specify, formally, the *constraints* that are thought to govern the underlying physical–causal processes. The important difference between the different kinds of models lies not in their relation to the actual mechanism, but in what they presuppose concerning the *nature* of the mechanism. The tendency to equate representational models with mechanisms on the exclusion of alternatives may have to do with the fact that the utilization of representations is the *standard* cognitivist way of creating a mechanism: viz., it is the standard way of creating a computational model that shows behavior similar to the cognitive phenomena of interest. However, a dynamical model is utilized in exactly the same way. *Both* kinds of models can be implemented in computers, and in both cases the resulting behavior is to be compared to the cognitive phenomena studied. The ultimate question regarding the proposed mechanisms, of course, is simply *which* mechanism is instantiated by the cognitive system. We see no reason to suspect that the brain is less fit to implement dynamical than representational models (if anything, the contrary seems more likely). Since the characterizations of models can play an important (heuristic) role in neuroscientific research, we think having an alternative non-representational mechanism available for certain cognitive phenomena is of great importance to cognitive science. Of course, an important reason to use representations has been that no other account of cognitive behavior with a comparable formal rigor was available. The question “can this behavior be explained without using representations?” has been close to a rhetorical one over the last few decades. We feel, however, that the recent rise of DST may end this situation. To be sure, we do not doubt that representations have played an important role in the explanation of cognitive behavior and that they will continue to do so. Yet, we claim that in every case of cognition one has to ask the question whether representations are *necessary* to explain the phenomena at hand, before one starts building models on the basis of them. The successes of the representational approach should not blind one to the importance of this question. One is reminded of the astronomers who, following Plato, started their investigations of the heavens on the assumption that the movement of the stars and planets was bound to be circular. And although the Ptolemaic system was capable of explaining most of the observable phenomena by means of this undisputed assumption, the question whether circles were really necessary to account for this class of observable phenomena turned out to be a good one to ask.

Cognitive science has made large steps forward in understanding human behavior. One of the main reasons for this was that the representational approach made it possible to build formal models that could be used to generate and test hypotheses. In a fruitful interaction between experimental data and mathematical models, the understanding of cognitive behavior improved at a high speed. Representational cognitive science was all the more successful

because alternative views experienced great difficulties in constructing models at a similar level of formalization. It is, however, precisely in this respect that we value the DST approach, because it does provide a reasonable, formalized, model-oriented, and empirically applicable alternative explanation of behavioral and cognitive phenomena. The present paper indicates that this approach can be applied even to a case of representation-hungry cognition.

Notes

1. Thus, the label ‘traditional cognitive science’ encompasses classical models based on symbolic representations (e.g., Fodor, 1975; Newell, 1980) and standard connectionist models based on distributed representations (e.g., Smolensky, 1988; Van Gelder, 1992). Although connectionist models are often dynamic in nature, many models still confer to the traditional representational approach. Port and Van Gelder (1995, pp. 3, 34) for instance say about connectionism’s bible (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986) that “the classic PDP style connectionism is little more than an ill-fated attempt to find a half-way house between the two world-views (. . .). Much standard connectionist work (e.g., modeling with layered backprop networks) is just a variation on computationalism, substituting activation patterns for symbols.” See also Clark (1997, pp. 58–59), Thelen and Smith (1994, p. 42), and Freeman (1995, p. 117).
2. The drift, v , in the random walk is assumed to be a Gaussian random variable with mean $\mu_v = f(dV/dx)$ and standard deviation σ_v . It is assumed that on each discrete time step the random walk proceeds by moving a “step” left on the x -axis ($v < 0$) or right ($v > 0$) or stay at the same position on the x -axis ($v = 0$).
3. Tuller et al. (1994) specified a slightly different relationship between the control parameter k and the experimental variable λ . First, they included a *step function* for the effect of repetitions; i.e., repetitions were assumed to take effect only after some *critical* number of repetitions were reached. Second, they defined the influence of λ as *adding* to the initial value of the control parameter k within a coupled sequential run (denote by k_0 by Tuller et al.). We simply define k as a direct function of λ for each trial. Third, Tuller et al. incorporated in their equation the value of λ at the other extreme from its initial state (denote by λ_f by Tuller et al.). We believe that our specification is simpler and qualitatively equivalent to Tuller et al.’s specification at the level of analyses performed by both Tuller et al. and ourselves. That is, we, like Tuller et al., test mainly for *qualitative* predictions of the model, and these qualitative data cannot decide which specification is better. Finally, we felt the need to include the parameter λ_{t-1} to account for the *contrastive* influence of the *length* of a rod on the preceding trial in random sequences. Possibly the fact that Tuller et al. (1994, p. 5) found mixed results when testing for local assimilative and contrastive effects in random sequences may be due to the fact that they did not correct for this factor in their analyses. We would like to note that the apparent differences between Tuller et al.’s and our model are in a sense irrelevant for the main thesis of this article. Supporting DST as an approach to modeling of imagined action does not imply commitment to any particular form of Eq. (2).

4. Psychophysics studies (see, e.g., [Morgan & Watt, 1989](#)) suggest that the Weber fraction ($\Delta I/I$) for length discrimination is approximately 0.05. Given that the increment used in our experiment was only 1.5 cm, the fraction between the increment and rod-length consequently ranged from 0.026 (viz., 1.5 cm/75.0 cm) to 0.016 (viz., 1.5 cm/91.5 cm). This means that the direction of parameter change is presumably not perceivable for participants from one trial to another (at least, in a sequential condition). On most occasions the fact that the hand-held rod is longer or shorter than a preceding rod does not become apparent within less than three or more trials.
5. Since additional switches, by definition, occur before the “last switch point,” and “enhanced contrast” was the most common effect in coupled sequential runs, additional switches tended to occur in the “lower half” (viz., before the last switch point) in increase runs, and in the “upper half” of decrease runs. Graphs plotting number of additional switches against rod-length do not indicate a strict separation though. This may be due to the fact that individual data are too noisy, and that averaging over participants makes the separation invisible (because every participant has a different 50% point). This is why we chose to just test for associations between different conditions, with total number of additional switches as the dependent variable.
6. Because the scores on ($\text{Max}_{\text{no}} - \text{Min}_{\text{yes}} + 1.5$) were not normally distributed (viz., a mode located at zero) we chose to do a randomization test instead of an ANOVA. The randomization test is a non-parametric alternative to ANOVA, and hence does not make any assumptions about how scores are distributed ([Edgington, 1986](#)). In our randomization test, we used 5,000 randomly sampled permutations of the dataset as a reference set.

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